Can local environmental constraints improve enterprise's green innovation quality? Evidence from Chinese listed firms

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Title page

Can local environmental constraints improve enterprise's green innovation quality? Evidence from Chinese listed firms

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Abstract

This study investigates how local environmental target constraints, a distinctive characteristic of Chinese environmental regulations, drive enterprises to improve their green innovation quality. We empirically examine the mechanism of the impact of the intensity of different types of local environmental target constraints on the quality of corporate green innovation utilizing the data of A-share listed companies in Shanghai and Shenzhen in China from 2011-2019 and each city's Government Work Reports. First, the strength of indirect environmental target constraints has a significant positive effect on the quality of green innovation, but further nonlinear characteristics reveal a significant inverse U-shaped relationship between them. However, direct environmental target constraint intensity had significant effects in improving enterprises' green innervation quality. Second, indirect environmental target constraint intensity has an inverted U-shaped trend in increasing the intensity of environmental regulation and influencing the digitalization of enterprises, which in turn forms an inverted U-shaped relationship with the quality of green innovation. Under indirect environmental goal constraint intensity, the increase in R&D expenditure for green innovation quality improvement decreases the expected net income, resulting in insufficient incentive for innovation, which explains the marginal decreasing trend of the positive impact of indirect environmental goal constraints on the quality of green innovation. Third, indirect environmental target constraint intensity works better in areas with policies prioritizing city over province and with mayors less than 57 years old. Therefore, local governments should establish an environmental target constraint system based on indirect environmental target constraints complemented by direct environmental target constraints, and assess and report the performance of indirect environmental targets in the subsequent Government

Work Report. Further reforms should streamline administration, decentralize power and improve services, cultivate more young and knowledgeable cadres, encourage communication and exchange between governments and enterprises, and implement market-oriented environmental regulations and measures such as emission trading mechanisms.

Keywords: Environmental target constraint; Green innovation quality; Environmental accountability system; Environmental regulations

1. Introduction

China made prominent progress in increasing its economic growth during the opening up over the past 40 years.¹ However, the extensive economic development mode creates a heavy burden on the ecological environment. In April 2019, the State Development and Reform Commission and the Ministry of Science and Technology of China promulgated the *Guiding Opinions on Establishing Market-oriented Green Technical Innovation System*, wherein, the phrase “green technical innovation” appeared for the first time in a programmatic document by the China Communist Party and later appeared in the October 2021 *Action Plan for Carbon Dioxide Emission Peaking Before 2030* issued by the State Council, which lists “innovations in green and low-carbon science and technology” as a major task. Thus, we understand that green innovation by enterprises is an important aspect of an ecological civilization and a critical path to realizing the carbon emission peak and carbon neutrality, as well as achieving high-quality economic development that provides both financial and ecological benefits. However, enterprises still face problems in green

¹ Abbreviations:

CNRDS: China National Research Data Service Platform

IPC: International Patent Classification

S&T: Science & Technology

70 innovation quality because the novelty, inventiveness, influence, and practical value of their
71 innovations are relatively low due to an imperfect patent system, distortion effects of some
72 industrial incentive policies, and great difficulties and long cycles typical of innovation activities.

73 To accelerate the socialist construction of an ecological civilization, the State Council
74 promulgated the *Decision on Implementing Scientific Development Outlook and Furthering*
75 *Environmental Protection* in December 2006, which stipulated that the KPIs of emission cuts
76 would be taken into account when promoting or rewarding cadres. The Method for Assessing
77 Reduction of Major Pollutants Emissions introduced the mechanisms of environmental protection
78 accountability and the one-vote veto to assess local cadres' performance in reducing the emissions
79 of major pollutants more strictly. Then, the local environmental target constraint system began to
80 take shape and was further improved during the 12th and 13th five-year periods. The local
81 governments' environmental target constraints have Chinese characteristics and account for
82 environmental protection when assessing local governments' political performance. These will
83 directly influence the actions of local governments and impact enterprises' green innovations.
84 Recent studies explored the influence of environmental protection accountability mechanisms on
85 enterprises' green and technical innovation (Tao et al., 2021; Yu et al., 2020), though they
86 examined only the external impacts in terms of whether or not they were implemented. There is no
87 systematic and thorough research on the influence mechanism and the incentive effects of different
88 local environmental target constraint intensities on enterprises' green innovation quality.
89 Moreover, currently, local governments at different levels have not set detailed pollution-reducing
90 targets as they have done to save energy and reduce CO₂ emissions. There is still more room to
91 improve the policies related to environmental target constraints. The policy-making process should

be standardized, and the targets should be more specific and comprehensive. Therefore, exploring the mechanism using local environmental target constraint intensity to influence enterprises' green innovation quality and optimizing the policy mechanism of local environmental target constraints driving high-quality development of green innovation in enterprises is both theoretically and practically significant for promoting socialist ecological civilization construction, realizing peak carbon emissions and carbon neutrality, and achieving high-quality economic development.

When discussing the relationship between environmental policies and enterprises' green innovations, most prior studies analyzed the influence of environmental regulations on enterprises' green innovations from the macro view of regions and the meso-view of industries. The definition and measurement of environmental regulations are relatively broad, and generally use reduced pollutant emissions and pollution treatment expenses as proxy variables. Only a few studies combine environmental policies with governments' environmental accountability assessments. Therefore, the existing literature is missing an analysis of governmental environmental targets in terms of the influence of governments' voluntary constraints on enterprises' green innovation quality. To determine the effects of different local environmental target constraint intensities on enterprises' green innovation quality and whether the effects possess linear features, we innovatively construct indicators of local environmental goal constraint intensity from the perspective of the environmental protection goal responsibility system, based on actual local government environmental goal constraint assessments. We build a theoretical model to study the influence of local environmental constraint intensity on enterprises' green innovation using the micro data of green patent classification numbers from A-share listed companies on the Shanghai and Shenzhen Stock Exchanges and the Government Work Reports of cities for 2011-2019. We

thus empirically examine the mechanism by which different local environmental target constraint intensities influence enterprises' green innovation quality at the micro-firm level.

This study offers several marginal contributions. First, in terms of the research approach and questions, our study based on the environmental accountability system, which has prominent Chinese characteristics, accounts for both environmental policies and governments' target constraint behaviors to explore the influence of local environmental target constraint intensity on enterprises' green innovation quality and its nonlinear features. By clarifying the research questions and objects, this study not only complements the theoretical studies on the influence of Chinese environmental policies on enterprises' green innovations, but also sheds light on the differing influence of various types of environmental regulations on enterprises' green innovation quality. We reexamine the Porter Hypothesis on the basis of Chinese experiences and evidence. Second, with respect to research objects, we follow the concept of "environmental target constraints" to create different indicators of local environmental target constraint intensities with reference to the environmental targets set in the Government Work Reports of various cities and environmental performance released in public reports. We also use data on listed companies' green patent classification numbers to measure their knowledge width and use it as a proxy variable for enterprises' green innovation quality to augment prior studies on enterprises' green innovation quality. Third, in terms of sampling, most studies on environmental policies and enterprises' green innovations are at the macro or meso levels. We conduct a micro-study using data on listed companies, which, to some extent, can reduce the aggregation bias of macro data and provide robust empirical support for studies on the effects of local environmental target constraint intensity on enterprises' green innovation quality. Fourth, after effectively identifying the influence of local

environmental target constraint intensity on enterprises' green innovation quality, we adopt the macro view of cities and the micro view of enterprises to examine the mechanism of action between environmental regulations and S&T expenditure of the government and enterprises' media exposure, social responsibility, R&D investment, digitalization, and financing. Therefore, this study offers a new theoretical interpretation of how local environmental target constraints affect enterprises' green innovation quality. Finally, the results of this study provide local governments with constructive suggestions on encouraging enterprises to pursue high-quality green development by setting reasonable environmental target constraint intensities and optimizing the design and implementation of environmental target constraint policies.

2. Literature review

In terms of the impact of local governments' environmental target constraints on corporate green innovation, most studies are based on the Porter Hypothesis. Kammerer (2009) empirically concluded that environmental regulations not only drive innovation in green products and encourage extensive use of green products, but also promote their novelty, which lends solid support to the Porter Hypothesis (Cohen and Tubb, 2018; Porter and Van Der Linde, 1995). After the government implements suitable environmental supervision, enterprises may choose to adopt strategies to meet environmental supervision requirements and actively carry out green technical innovations to reduce pollutant emission, optimize production process, and effectively reduce pollutant-discharging costs (Rubashkina et al., 2015). Presently, most studies focused only on regional data indicators, such as environmental enforcement (Fan and Zhao, 2019), reduced regional pollutant-discharge volume (Wang et al, 2018), and comprehensively weighted indicators of environmental governance investment (Wei et al., 2017). These studies explored the relationship

between environmental regulations and green innovation at the meso-industrial and macro-regional levels. A few scholars adopted a microscopic perspective to study the influence of governments' environmental awareness on enterprises' green innovations. For example, Fang et al. (2021) conducted research on the new *Environmental Protection Law* and found that it will put heavily polluting enterprises under supervisory pressure, potentially driving them to improve the quality of information disclosure and pursue green innovation. Liu et al. (2021) also found that enterprises filed more applications for more inventive and utility model environmental patents after the implementation of the new *Environmental Protection Law*. Sun et al. (2020) studied 132 enterprises from 16 heavily polluting industries and found that environmental regulations would encourage enterprises to invest more in environment-friendly R&D. However, some scholars oppose the Porter Hypothesis, which states that environmental regulations inhibit corporate green innovation. Kemp and Pontoglio (2011) held that enterprises will switch focus to environmental management projects in order to meet governments' environmental requirements, which may incur higher costs and crowd out financial resources for R&D and technical innovations. He et al. (2021) concluded that environmental regulations will create a crowding-out effect on enterprises' R&D investment and negatively impact their patent output. Testa et al. (2011) also argued that environmental regulations such as pollutant-discharging fees will not benefit enterprises in carrying out technical innovations. Therefore, an increasing number of scholars realize that the influence of environmental regulations on enterprises' green innovations might be nonlinear and heterogeneous (Rexhäuser and Ramer, 2014). Wang et al. (2020) found that the influence of environmental regulations on enterprises' green innovations has an inverted U-shape. Jiang et al. (2018) defined environmental regulations from the two dimensions of industry and region, and

discovered the negative effects of industrial supervision on innovation performance, as opposed to regional regulation, which contributes to innovation performance. Li and Xiao (2020) comprehensively observed the incentive role of heterogeneous environmental regulations for encouraging enterprises to pursue green innovations and agreed that pollutant-discharging fees would force enterprises to conduct green innovation while environmental grants will have a crowding-out effect on enterprises' green innovation capability. Wu et al. (2021) argued that the design and enforcement of environmental regulations must account for enterprises' actual conditions and differences to encourage them to pursue green innovations.

In summary, existing research has several gaps. First, the relationship between environmental policy and corporate green innovation has not yet reached a unified consensus, and there are significant differences in the effects of various types of environmental regulation on corporate green innovation. The Porter Hypothesis is supported by foreign environmental regulatory policy systems dominated by market-based environmental regulations. In comparison, most of China's environmental regulations are currently mandatory (Wang et al., 2015). Local officials not only make but also implement these mandatory environmental regulations. Currently, few studies account for both environmental policies and governments' environmental accountability assessments, and there is a lack of research examining the government's autonomous environmental goal constraints. Second, most of the current studies on environmental regulation in China are based on the macro level, which does not directly reflect their Chinese characteristics or provide a broad definition and measurement of China's environmental regulations. Studies using reduced pollutant-discharge volume and pollution treatment cost as proxy variables cannot evaluate and examine the effectiveness of different environmental regulations accurately, nor

differentiate and summarize the heterogeneous influence of different environmental regulations. Third, most studies on environmental policies and enterprises' green innovations are conducted from a macro-regional or meso-industrial perspective, and empirical examinations at the macro-regional and meso-industrial level have relatively larger deviations. The scarce studies on micro-enterprises' green innovations always focused on the number of green patents. There are few studies that concentrate on enterprises' green innovation quality at the micro level. Fourth, Yu et al. (2020) and Tao et al. (2021) empirically examined the influence of environmental accountability on enterprises' technical and green innovations; however, their studies focused only on macro-regulations and assessed their exogenous impacts based on whether the regulations were implemented. They did not subclassify or quantitatively measure the constraints of different environmental targets. There is much more scope to systematically and deeply understand the influence and incentive power of the intensities of various environmental target constraints on enterprises' green innovation quality. The indirect reaction mechanism is yet to be discovered, and the empirical design of its effect needs to be optimized urgently.

3. Influencing mechanism and theoretical model

3.1 Mechanism of the effect of local environmental target constraints on green innovation quality

3.1.1 Direct influence

When local governments at all levels make environmental targets public and assess their achievement, it reinforces the importance of environmental management in the political tasks of local governments, which in turn drives them to introduce environmental management measures, the most typical of which is the "closure and transfer" of enterprises (Chen et al., 2018a). Facing

stringent environmental controls and standards, enterprises with financial and technological capabilities will choose green innovations to transform and upgrade their development (Milani, 2017). Innovation quality is key to enterprises' interests. On the one hand, to earn more from their green innovations, enterprises will cultivate unique competitive advantages and stimulate themselves. On the other hand, facing fierce market competition and strict government environmental supervision, enterprises under pressure from governmental environmental performance assessments and heterogeneous environmental regulations will honor their social responsibilities by enhancing the quality of their green innovations.

Therefore, we propose **Hypothesis 1:** *Local governments' environmental target constraint intensity will significantly improve enterprises' green innovation quality.*

3.1.2 Indirect influence

At the macro-mechanism level, Yu et al. (2020) held that local environmental target constraints will enhance the rigidity of environmental regulations to encourage technical innovation. However, the positive action of environmental target constraint intensity on enterprises' green innovation quality may change dynamically. First, although the implementation of command-based environmental regulations will have a certain promotion effect on enterprises' green innovation initially, due to the existence of penalty caps, it is likely that some enterprises will be satisfied with "meeting the standards" of green innovation activities; that is, the compensation benefits resulting from innovation activities will converge with the mandatory penalty costs caused by environmental non-compliance. Thus, there will be no effective incentive for enterprises to further improve the quality of green innovation. Command-based environmental regulations raised the environmental costs of the production process, which encroach on resources for green

innovations (Petroni et al., 2019). Second, when incentive-based environmental regulations such as environmental taxes and grants improve, enterprises will increase their investment in green innovation (Bi and Yu, 2016), which has a certain "resource compensation effect" (Li and Xiao, 2020) on corporate green innovation, which in turn is conducive to improving the quality of green innovation. However, given the government's information disadvantage on enterprises' green innovation activities, responsive and strategic innovation behaviors arise. As the distortionary effect of resource allocation due to environmental taxes becomes greater than the ameliorating effect of negative environmental externalities, enterprises will reduce their R&D investment in green innovation when they reach a certain level (Zhang et al., 2017), or even engage in low-effort pursuits of a short-term increase in the quantity of green innovation and low-quality innovation to gain short-term green innovation quantity (Tao et al., 2021). In particular, when the marginal benefits generated by green innovation gradually decline (Xu et al., 2012), and the R&D investment and marginal cost for enterprises to maintain high-quality green innovation gradually increase, coupled with the increasing difficulty and risk of high-quality green innovation, the incentive for enterprises to further improve the quality of green innovation will decrease significantly.

Therefore, we propose **Hypothesis 2:** *By increasing the rigidity of environmental regulations, local environmental target constraint intensity creates an inverted U-shaped relationship with enterprises' green innovation quality.*

Local officials, faced with the pressure of short-term performance appraisal, are more inclined to choose methodological initiatives that yield faster results in the short term to gain significant short-term results (Li and Li, 2020). However, it usually takes 3-5 years for a green innovation to

develop from design to application, while it has a long cycle before improving environmental pollution and certain risks (Bian and Bai, 2017), which is especially true for high-quality green innovations. Therefore, pressed by environmental target constraint assessments, local officials with elastic tenures tend to increase environmental protection expenditures that are more effective and shorter in the direct treatment of environmental pollution (Li and Bai, 2021) and cut expenses for technical innovations that show unclear effects in tackling environmental pollution and are slow to translate into actual application. Therefore, increased local environmental target constraint intensity will crowd out the government's S&T expenses, and enterprises will face heightened costs to pursue high-quality green innovations, which may deter enterprises from enhancing the quality of green innovations.

Therefore, we propose **Hypothesis 3:** *Increased local environmental target constraint intensity will cut the government's S&T expenses and inhibit enterprises from pursuing high-quality green innovations.*

At the micro-mechanism level, the environmental accountability system guides the media and public to focus more on environmental protection (Tao et al., 2021), which puts enterprises under stricter environmental supervision and alerts enterprises' executives to related risks (Snyder and Stromberg, 2010). Social opinions and media supervision force enterprises to invest more resources into green innovations (Fan and Fu, 2021). Environmental initiatives and attention from the public and media will stimulate enterprises to increase investment in environmental protection (Wang and Li, 2017), which will help enhance their sense of social responsibility and normalize their environmental behaviors (Han et al., 2021). By voluntarily fulfilling their social responsibilities to meet stakeholders' expectations for environmental protection, enterprises not

only closely follow social values and regulations (Han et al., 2021), but also build their brands and images and elevate their performance (Wang et al., 2015). Enterprises with enhanced awareness of social responsibility will invest more in R&D with prominent social benefits (Engida et al., 2020). Therefore, to meet both economic interests and social values, enterprises will set environmental targets and develop long-term green development strategies to voluntarily pursue breakthrough green innovations with higher quality. The institutional background of environmental target constraints and media opinion supervision, coupled with the national policy call for "promoting the deep integration of science and technology innovation with the real economy" creates a favorable economic and political environment and orientation to motivate enterprises to further increase their R&D investment to improve the quality of green innovation and increase stakeholders' confidence in the enterprises' green development (Xu et al., 2016).

On the one hand, environmental target constraints increase the rigidity of environmental regulations. Enterprises must comprehensively and transparently disclose environmental information, which will guide investors to pay attention to enterprises' green technical innovation and applications, and help enterprises acquire financial support for their green technical R&D through legitimate means (Wang et al., 2018). On the other hand, under the environmental target constraint system, green credits, carbon financing, and other market-oriented financial instruments keep improving and growing, which under influence of relevant policies, were connected extensively with enterprises' green innovations (He et al., 2021). Additionally, the environmental accountability system boosts public confidence in enterprises' environmental expenditures and signals investors to provide support to green innovations, which indirectly helps mitigate the financing constraints enterprises face in carrying out green innovations (Pan et al., 2021). After

mitigating their financing constraints, enterprises under pressure from mandatory environmental regulatory tools like compulsory pollutant-discharge standards and fees will be forced to carry out technical innovations to control their pollutant-discharge costs and save environmental costs. When compensation from innovations exceeds compliance costs, enterprises increase the R&D expenditures (Ma et al., 2018). Simultaneously, enterprises gain a competitive advantage and reduce the energy consumption and emissions through technological innovation, which is more helpful for enterprises to benefit under a market-oriented environmental regulation system, such as the emission trading mechanism (Sun et al., 2020), which further motivates enterprises to increase their R&D expenditures. Increased R&D expenditure and innovation input will ensure enterprises' continuous and steady participation in high-quality green innovations with longer cycles and deeper and broader influence.

Therefore, we propose **Hypothesis 4**: *Local environmental target constraint intensity will press enterprises to improve green innovation quality by increasing their media exposure, enhancing their awareness of social responsibility, boosting their R&D expenditure intensity, and mitigating their financing constraints.*

Under pressure from environmental accountability and the integration of the digital economy with the real economy, digital transformation becomes a win-win choice for enterprises to address both profitability and environmental protection (Yuan et al., 2021). Enterprises' digital transformations will optimize the energy consumption structure (Ren et al., 2021), productive techniques and processes, production efficiency, and R&D efficiency (Lin and Zhou, 2021), and facilitate knowledge spillover (Zhao et al., 2020), which will effectively drive enterprises to extend the breadth of their knowledge of green innovations. However, as local environmental target

constraint intensity increases, local governments are inclined to crowd out S&T expenditure to enhance environmental performance more directly and quickly to increase environmental governance expenditure, which is adverse to the digital transformation of enterprises (Wu et al., 2021). Moreover, the process of digital transformation will slow down when transformation becomes increasingly difficult, and overdue renewal of infrastructure and technologies will leave enterprises at a lower level of digitalization. The positive effect of local environmental target constraint intensity on enterprises' digital transformation will marginally and progressively decrease, which gradually slows enterprises' green innovation quality improvement.

Therefore, we propose **Hypothesis 5**: *There is an inverted U-shaped relationship between local environmental target constraint intensity and the degree of enterprise digitalization, which creates the effect of local environmental target constraints on the quality of enterprise green innovation, which also follows an inverted U-shaped curve.*

3.2 Theoretical model

We construct the theoretical model mainly by following the mechanism path by which local environmental target constraints will influence enterprises' green innovation quality by increasing the rigidity of environmental regulations. Local environmental target constraint intensity directly reflects local governments' attentiveness, resoluteness, and executive power in environmental governance. There are three scenarios in which environmental target constraints through environmental regulations affect enterprises' green innovation quality: (i) the influence of environmental taxes on enterprises' green innovation quality, (ii) the influence of auctioned emission rights on enterprises' green innovation quality, and (iii) the influence of emission rights trading on enterprises' green innovation quality. We borrow the theoretical framework of Xu et al.

(2012), in which under the hypothesis of rational economic actors, enterprises maximize value and minimize costs under given incomes when facing local government environmental target constraints. Under this hypothesis, we explore the influence of environmental taxes, emission rights for auctions, and emission rights trading on enterprises' green innovation quality.

3.2.1 Influence of environmental taxes on enterprises' green innovation quality

Facing environmental taxes, enterprises will increase costs in three ways. (1) Environmental tax costs, $T \bullet p$, where T represents the environmental tax rate and p represents the volume of discharged pollutants declared by enterprises. (2) Emission reduction costs, $\alpha \bullet \varphi(e)$, where α represents green innovation quality, $\varphi(e)$ represents the enterprises' emission reduction function, and e represents enterprises' reduced emissions. $\varphi(e)$ is a monotonically decreasing function of e and $\varphi''(e) > 0$. (3) Penalty cost, $\pi \bullet \omega(e - p)$, where π represents the probability that the enterprise is found to be paying insufficient environmental tax. $\omega(e - p)$ represents the functional relationship between the penalty amount administered to enterprises and their undeclared emission volume; both $\omega'(e - p)$ and $\omega''(e - p)$ are greater than 0. In a fully competitive market, enterprises i and j have similar characters and features. Presuming that $\alpha_i > \alpha_j$, equations (1) and (2) represent enterprise i 's cost function and enterprise j 's cost function, where v_j represents the extra cost incurred to enterprise j when trying to catch up with enterprise i in green innovation quality.

$$C_i = T \bullet p_i + \alpha_i \bullet \varphi(e_i) + \pi \bullet \omega(e_i - p_i) \quad (1)$$

$$C_j = T \bullet p_j + \alpha_j \bullet \varphi(e_j) + \pi \bullet \omega(e_j - p_j) + v_j \quad (2)$$

By constructing the Lagrange function, we can calculate the minimum value of the cost function of enterprise i :

$$L = T \bullet p_i + \alpha_i \bullet \varphi(e_i) + \pi \bullet \omega(e_i - p_i) - \lambda \bullet (e_i - p_i). \quad (3)$$

According to the Kuhn-Tucker conditions, we know the optimal emission volume and undeclared emission volume of enterprise i :

$$e_i^* = \{e_i \mid \alpha_i \bullet \varphi'(e_i) + T = 0\} \quad (4)$$

$$(e_i - p_i)^* = \{(e_i - p_i) \mid T - \pi \bullet \omega'(e_i - p_i) = 0\}. \quad (5)$$

Similarly, we have the optimal emission volume and undeclared emission volume of enterprise j :

$$e_j^* = \{e_j \mid \alpha_j \bullet \varphi'(e_j) + T = 0\} \quad (6)$$

$$(e_j - p_j)^* = \{(e_j - p_j) \mid T - \pi \bullet \omega'(e_j - p_j) = 0\}, \quad (7)$$

where $\alpha_i > \alpha_j$, $\varphi'(e) < 0$, and $\varphi''(e) > 0$, are under the same environmental tax rates, and $e_i^* > e_j^*$ and $(e_i - p_i)^* = (e_j - p_j)^*$. Therefore, $p_i^* > p_j^*$. Presuming α_j is the green innovation quality of enterprise i , its net income is

$$(e_i - p_i)^* = (e_j - p_j)^* \\ \Delta I = \alpha_i \bullet \varphi(e_i^*) - \alpha_j \bullet \varphi(e_j^*) + \omega((e_i - p_i)^* - (e_j - p_j)^*) + T \bullet (p_i^* - p_j^*) - \nu_j. \quad (8)$$

Then, we find $p_i^* - p_j^* = e_i^* - e_j^*$, and we can simplify the equation above into

$$\Delta I = \alpha_i \bullet \varphi(e_i^*) - \alpha_j \bullet \varphi(e_j^*) + T \bullet (e_i^* - e_j^*) - \nu_j. \quad (9)$$

When $\Delta I \geq 0$, enterprise i will improve its green innovation quality to α_i . The expected net income ΔI of enterprise i includes the part of the emission reduction cost reduced due to improved green innovation quality, the part of environmental tax reduced due to improved green innovation quality, and the part of the cost added to improve green innovation quality. If enterprise i 's cost to improve green innovation quality is less than the sum of the decrease in emission reduction cost and decrease in environmental tax, then enterprise i will improve its green

innovation quality. We can calculate T 's first derivative using ΔI as follows:

$$\begin{aligned} d\Delta I / dT = & \alpha_i \bullet \varphi'(e_i^*) \bullet d(e_i^*) / dT - \alpha_j \bullet \varphi'(e_j^*) \bullet d(e_j^*) / dT \\ & + (e_i^* - e_j^*) + T \bullet (d(e_i^*) / dT - d(e_j^*) / dT) \end{aligned} \quad (10)$$

Under the optimal emission volume, $T = -\alpha_i \bullet \varphi'(e_i^*) = -\alpha_j \bullet \varphi'(e_j^*)$, then, $d\Delta I / dT = (e_i^* - e_j^*)$.

Since $e_i^* - e_j^* > 0$, we find $d\Delta I / dT > 0$. Therefore, under the optimal emission volume, when environmental tax rates increase, enterprises' net income will grow as they improve their green innovation quality, which will render enterprises willing to enhance their green innovation quality.

Meanwhile, according to $e_i^* = \{e_i \mid \alpha_i \bullet \varphi'(e_i) + T = 0\}$, we know under the optimal emission volume,

$$\alpha_i = -\frac{T}{\varphi'(e_i^*)}. \quad (11)$$

Solving equation $d(\alpha_i) / dT = -\frac{1}{\varphi'(e_i^*)} > 0$, we find that under the optimal emission volume, increased environmental tax rates can effectively improve enterprises' green innovation quality, which is in line with the above conclusion.

3.2.2 Influence of emission rights for auction on enterprises' green innovation quality

In essence, emission rights for auctions refer to enterprises paying the government to acquire a quota of emissions within the scope of the distributable emission rights. Emission rights for auctions cannot be transferred to others, and if emissions exceed the licensed quota, then enterprises will be fined. Let us assume that P represents the price of a unit of licensed emission, l^0 is the emission quota acquired by the enterprise, and the declared emission volume is l . If the enterprise misreports its emission volume, then it will be fined. We can represent the functional relationship between the fine amount and undeclared emission volume as $\omega(\bullet)$. According to the previous analysis, in a fully competitive market, enterprises i and j have similar characteristics and

properties, and we can express their cost functions as follows:

$$C_i = P \bullet (l_i - l_i^0) + \alpha_i \bullet \varphi(e_i) + \pi \bullet \omega(e_i - l_i) \quad (12)$$

$$C_j = P \bullet (l_j - l_j^0) + \alpha_j \bullet \varphi(e_j) + \pi \bullet \omega(e_j - l_j) + v_j. \quad (13)$$

By constructing the Lagrange function, we can find the minimum value of enterprise i 's cost function:

$$L = P \bullet (l_i - l_i^0) + \alpha_i \bullet \varphi(e_i) + \pi \bullet \omega(e_i - l_i) - \lambda \bullet (e_i - l_i) \quad (14)$$

According to the Kuhn-Tucker conditions, we know the optimal emission volume and undeclared emission volume of enterprise i :

$$e_i^* = \{e_i \mid \alpha_i \bullet \varphi'(e_i) + P = 0\} \quad (15)$$

$$l_i^* = \{l_i \mid P - \pi \bullet \omega'(e_i - l_i) = 0\} \quad (16)$$

$$(e_i - l_i)^* = \{(e_i - l_i) \mid P - \pi \bullet \omega'(e_i - l_i) = 0\}. \quad (17)$$

Similarly, we have the optimal emission volume and undeclared emission volume of enterprise j :

$$e_j^* = \{e_j \mid \alpha_j \bullet \varphi'(e_j) + P = 0\} \quad (18)$$

$$l_j^* = \{l_j \mid P - \pi \bullet \omega'(e_j - l_j) = 0\} \quad (19)$$

$$(e_j - l_j)^* = \{(e_j - l_j) \mid P - \pi \bullet \omega'(e_j - l_j) = 0\}. \quad (20)$$

Presuming $\alpha_i > \alpha_j$, $\varphi'(e) < 0$, and $\varphi''(e) > 0$, under the same price of emission rights, we find $e_i^* > e_j^*$ and $(e_i - l_i)^* = (e_j - l_j)^*$. Presuming enterprise i has the green innovation quality of α_j , its net income is

$$\Delta I = \alpha_i \bullet \varphi(e_i^*) - \alpha_j \bullet \varphi(e_j^*) + P \bullet (e_i^* - e_j^*) - v_j. \quad (21)$$

When $\Delta I \geq 0$, enterprise i improves its green innovation quality. When the enterprise has its optimal emission volume, $P = -\alpha_i \bullet \varphi'(e_i^*) = -\alpha_j \bullet \varphi'(e_j^*)$, and we solve the following equation:

$$d\Delta I / dP = (e_i^* - e_j^*) > 0. \quad (22)$$

When emission rights prices rise, enterprises can harvest more net income by improving their green innovation quality; therefore, they will be more willing to enhance green innovation quality.

Similarly, according to $e_i^* = \{e_i \mid \alpha_i \bullet \varphi'(e_i) + P = 0\}$, we find that under enterprises' optimal emission volume:

$$\alpha_i = -\frac{P}{\varphi'(e_i^*)}. \quad (23)$$

Solving $d\alpha_i / dP = -\frac{1}{\varphi'(e_i^*)} > 0$ reveals that under the optimal emission volume, an increase in the prices of emission rights can effectively encourage enterprises to improve green innovation quality, which supports the above conclusion.

3.2.3 Influence of emission rights trading on enterprises' green innovation quality

For auctioned emission rights, the government sets the price P , and it is an exogenous variable. However, when emission rights are traded freely in the market, the price is decided by the market and becomes an endogenous variable. Let us assume that the number of enterprises in the market is n ; the total quota of emission rights given by the government for free is L ; each emission rights unit will allow the enterprise to discharge one unit of pollutants; and when traded freely in the market, the price of a unit of emission rights is P . If enterprises i and j have similar characteristics and properties in a fully competitive market, then the amount of free emission rights quota given by the government to enterprise i is l_i^0 , and the emission volume reported by enterprise i is l_i ; therefore, we can find the initial equilibrium condition for the emission license market as follows:

$$\sum_{i=1}^n l_i(P, \pi, \alpha_i) = \sum_{i=1}^n l_i^0 = L. \quad (24)$$

464 Following the previous discussion, we assume that enterprise j 's green innovation quality is
 465 α_j . There are the I number of enterprises in the market committed to improving their green
 466 innovation quality to α_i ; and there are $n-I$ enterprises maintaining their green innovation
 467 quality at α_j ; $\alpha_i > \alpha_j$; and the total quota of emission rights is still L . Then, we can express the
 468 conditions for reaching equilibrium in the emission markets as

$$469 \quad \sum_{i=1}^I l_i(P^*, \pi, \alpha_i) + \sum_{j=I+1}^n l_j(P^*, \pi, \alpha_j) = L. \quad (25)$$

470 According to the previous discussion, $l_i > l_j$; if $P^* = P$, then we have

$$471 \quad \sum_{i=1}^I l_i(P, \pi, \alpha_i) + \sum_{j=I+1}^n l_j(P, \pi, \alpha_j) < L. \quad (26)$$

472 When the market is rebalanced, the equilibrium price is $P^* < P$. Considering equation (22),
 473 when the market reaches its equilibrium price, the emission rights price and the expected income of
 474 the enterprise fall. If α_i and α_j remain unchanged, then we can solve equation (25) to obtain the
 475 partial derivative of P^* in relation to I .

476 First, after calculating the partial derivative of L in relation to I and P^* in equation (25), we
 477 find

$$478 \quad \frac{\partial L}{\partial I} = l_i - l_j \quad (27)$$

$$479 \quad \frac{\partial L}{\partial P^*} = I \bullet \frac{\partial l_i}{\partial P^*} + (n-I) \bullet \frac{\partial l_j}{\partial P^*}. \quad (28)$$

480 Then, we find the partial derivative of P^* in relation to I :

$$481 \quad \frac{\partial P^*}{\partial I} = \frac{l_i - l_j}{I \bullet \frac{\partial l_i}{\partial P^*} + (n-I) \bullet \frac{\partial l_j}{\partial P^*}}. \quad (29)$$

482 Since $\frac{\partial e_i^*}{\partial P} = -\frac{1}{\alpha_i \bullet \varphi''(e_i)} < 0$, by equations (16) and (19), we have

$$\frac{\partial l_i^*}{\partial P} = \frac{\partial e_i^*}{\partial P} - \frac{1}{\pi \bullet \omega''(e_i - l_i)} < 0. \quad (30)$$

In the same way, we obtain

$$\frac{\partial l_j^*}{\partial P} = \frac{\partial e_j^*}{\partial P} - \frac{1}{\pi \bullet \omega''(e_j - l_j)} < 0. \quad (31)$$

According to the previous analysis, we know $l_i^* > l_j^*$; therefore, $\partial P^* / \partial I < 0$. Under optimal emissions, as the number of enterprises committed to green innovation quality increases, the price of tradable emission rights and the expected net income from improving green innovation quality keep falling, weakening the incentive for enterprises to increase their green innovation quality.

In summary, when local government target constraint intensity increases, environmental tax rates and the prices of the auctioned emission rights increase under the optimal emission volume, which increases the expected net income from improved green innovation quality and stimulates enterprises to boost green innovation quality. When an increasing number of enterprises pursue green innovation quality, the price of tradable emission rights falls and the expected net income from improved green innovation quality decreases marginally and progressively, which weakens the incentive to pursue green innovation quality. Therefore, the intensity of local environmental target constraints will form an inverted U-shaped relationship with the quality of enterprise green innovation by influencing the intensity of environmental regulations.

4. Research design

4.1 Empirical design

To investigate the influence of local environmental target constraint intensity on the quality of green innovation of enterprises, we match the data of listed enterprises according to the prefecture-level city in which they are registered to the prefecture-level city data. We construct the

504 following fixed effect model:

505
$$\ln GQ_{it} = \alpha_0 + \alpha_1 \ln SETC_{it} + \lambda \ln CV_{it} + d_f + d_j + d_t + \varepsilon_{it}, \quad (\text{Model 1})$$

506 where GQ_{it} represents the quality of green innovation; $SETC_{it}$ represents local environmental target
507 constraint intensity; CV_{it} represents the control variables; i and t indicate the company and year,
508 respectively; f represents the enterprise's industry, j represents the enterprise's prefecture-level
509 city, d_f represents industry fixed effects, d_j represents city fixed effects, d_t represents time fixed
510 effects, and ε_{it} represents the random error term.

511 According to the theoretical analysis above, we can conclude that the impact of local
512 environmental target constraint intensity on enterprise green innovation quality may have an
513 inverted U-shaped change trend. Hence, we add the quadratic term ($SETC_{it}^2$) of constraint intensity
514 of local environmental objectives into the benchmark regression model, as follows:

515
$$\ln GQ_{it} = \alpha_0 + \alpha_1 (\ln SETC_{it})^2 + \alpha_2 \ln SETC_{it} + \lambda \ln CV_{it} + d_f + d_j + d_t + \varepsilon_{it}. \quad (\text{Model 2})$$

516 **4.2 Variables**

517 (1) Enterprises' green innovation quality (GQ). Following Li et al. (2021), we measure
518 knowledge width by the main classification numbers of listed companies' green patents to reflect
519 their green innovation quality. China's International Patent Classification (IPC) follows the format
520 "Section - Class - Subclass - Main Group – Subgroup;" for example, A01B01/10. Specifically, the
521 first letter of an IPC denotes one of the eight IPC sections, the 2nd and 3rd digits denote the IPC
522 class, and the 4th letter denotes the IPC subclass. As in the Herfindahl-Hirschman Index, we can
523 define enterprises' patent knowledge width at the main group level as follows:

524
$$GPK_{it} = 1 - \sum \left(\frac{Z_{imt}}{Z_{it}} \right)^2,$$

525 where Z_{imt} is the cumulative number of green invention patents and utility model patents applied for

526 by enterprise i under the main group m up to year t , and Z_{it} is the cumulative number of green
527 patents applied for by enterprise i under all main groups up to year t . The higher the value of GPK_{it} ,
528 the greater the knowledge width of enterprises' green patents and the better their green innovation
529 quality. For the regression analysis, we add 1 to GPK_{it} and take its logarithm. We should note that
530 we choose only green invention patents and utility model patents because appearance design
531 patents adopt different numbering methods from the invention and utility model patents, and thus
532 require a different calculation method, and compared to invention and utility model patents,
533 appearance design patents do not reflect the complexity of knowledge the enterprise used during
534 the patent-creation process and cannot adequately embody enterprises' self-innovating capability.

535 For the robustness check, we refer to Li and Zhao (2020) and measure green innovation
536 quality by the number of citations of green patents. Specifically, we use the number of citations two
537 years after the application (GPC_{it}) to measure enterprises' green innovation quality. We add 1 to
538 (GPC_{it}) and take its logarithm ($\ln GPC_{it}$) to perform the robustness check. As there are limited years
539 of data, we calculate the number of citations two years after the application only for 2011-2018.

540 (2) Local environmental target constraint intensity. The central government sets the initial
541 environmental targets and then delegates the environmental targets to provincial governments, who
542 in turn delegate them to municipal governments for execution. The lower governments report to the
543 higher government, and the higher governments have the right to hold the lower governments
544 accountable. Based on the vertical distribution of environmental targets and accountability in
545 environmental targets assessment, first, as in Yu et al. (2020), we collected and sorted the
546 Government Work Reports of every city for each year, and manually retrieved and arranged the
547 specific environmental targets mentioned in the Government Work Reports and fulfillment of the

548 targets mentioned in various public reports^a to gauge local environmental target constraint
549 intensity. Following Li et al. (2020), we divide local environmental target constraints into direct
550 environmental target constraints and indirect environmental target constraints. The former refers to
551 the targeted emission reduction of sulfur dioxide, oxynitrides, chemical oxygen demand, ammonia
552 nitrogen pollutants, and so on, specified by the local governments in their Government Work
553 Reports.² We use specific indicators of PM_{2.5} density, PM₁₀ density, days of good air quality,
554 environmental quality, and so on, though unspecified indicators of sulfur dioxide, oxynitrides, and
555 ammonia nitrogen pollutants, among others, are still indirect environmental target constraints.³ In
556 contrast to environmental target constraints, environmental target constraint intensity directly
557 reflects governments' attentiveness, input, and executive power in meeting environmental targets.
558 Based on the intensity analysis of Liu and Huang (2019), we use the ratio of the cities' actual
559 fulfillment of environmental targets to the original environmental targets as an indicator to measure
560 local environmental target constraint intensity,⁴ which includes both direct environmental target
561 constraint intensity ($SDETC_{it}$) and indirect environmental target constraint intensity ($SIETC_{it}$).
562 Only when local governments specified concrete environmental targets in the year (including
563 specific pollutants and their targeted values) in their Government Work Report and reported their

² For example, the Government Work Report of Yangquan City in 2012 has specific emission-cutting targets of "to reduce emission of COD, ammonia nitrogen, SO₂, soot and dust by 1.3%, 1%, 2%, 3%, and 3%," respectively. Its Government Work Report of 2013 released the fulfillment of the emission-cutting targets: "emission of COD, ammonia nitrogen, SO₂, soot and dust has been reduced by 4.18%, 0.78%, 7.12%, 5.96%, and 5.1%," respectively. This example is typical of direct environmental target constraints.

³ For instance, the Government Work Report of Benxi City in 2017 set the environmental target of "80% of days in a year will have good air quality", and its Government Work Report of 2018 (released in 2017) reports 318 days of good air quality and the environmental target is fulfilled. Therefore, we see an indirect environmental target constraint.

⁴ In calculation, we need to unify the units used in specific targets and their fulfillment values. For example, we need to unify the tons of emission reduction and percentage of emission reduction, and unify the number of days with good air quality and the percentage of days with good air quality, and so on. Additionally, if the Government Work Report mentions that its specific environmental target is to fulfil the same provincial environmental target, then given the environmental accountability between the provincial and municipal governments, we set the environmental target constraint intensity to 1.

fulfillment of the targets (including specific pollutants and actual fulfilled values) in the next year's Government Work Reports can we calculate the corresponding constraint intensity. If local governments did not release specific environmental targets, but reported fulfillment in the next year's work report, we then set the year's environmental target constraint intensity to 1; if local governments neither set concrete environmental targets nor released fulfillment statements or they disclosed only environmental targets but did not report fulfillment, then we set their environmental target constraint intensity to 0.

(3) Intermediate variables. (i) City-level intermediate variables include environmental regulation rigidity (ER_{it}) and governmental S&T output (GTE_{it}). (ii) Enterprise-level intermediate variables include enterprises' media attention (CMA_{it}), enterprises' social responsibility (CSR_{it}), enterprises' R&D intensity ($R\&D_{it}$), enterprises' digitalization level (CDT_{it}), and enterprises' financial constraints (FC_{it}).

(4) Control variables. (i) City-level variables include economic development level (GDP_{it}), human capital (HC_{it}), fiscal decentralization (FD_{it}), and traffic infrastructure (TI_{it}). (ii) Enterprise-level control variables include enterprise scope (CS_{it}), liability level (LL_{it}), remuneration/overall asset ratio (ROA_{it}), return on net assets (ROE_{it}), equity property (SOE_{it}), Tobin's Q ratio (TQ_{it}), fixed asset ratio (FA_{it}), current ratio (LR_{it}), enterprise competitiveness (EC_{it}), and cash flow level (CFL_{it}).

We matched the data of A-share listed enterprises on the Shanghai Stock Exchange and Shenzhen Stock Exchange from 2011 to 2019 to their green patent applications. From these samples, we removed enterprises without green patent applications from 2011 to 2019, finance and insurance enterprises, enterprises lacking relevant data, ST and PT enterprises, and insolvent

enterprises. For the remaining sample of 2,484 listed enterprises, we obtain the macro data of the cities in which they are registered. Listed enterprises' green patent classification data are from the State Intellectual Property Rights Bureau. We retrieved information on green patent citations from the database of listed enterprises' operational data from the China National Research Data Service Platform (CNRDS). We collected and sorted the data to calculate environmental target constraint intensity and environmental regulation rigidity manually from the cities' original Government Work Reports during the sample period. Enterprises' digitalization level data are from their yearly reports. The social responsibility data of enterprises are from Hexun Net. We obtained enterprises' media attention data from the Financial News Database of Chinese Listed Companies. The data for the other variables and calculations are from the China Stock Market & Accounting Research (CSMAR) database and the WIND database. Data for the remaining city-level variables are from the China City Statistical Yearbooks. We matched the local environmental target constraint intensity and city-level variables with enterprises' panel data according to the cities in which the listed enterprises are registered. Except for financial constraints and the nature of shareholding, we take the logarithms of the variables. Table 1 lists the variable definitions and calculation methods.

Table 1 Descriptive Statistics and Measurement of the Variables.

Variable	Variable measure	Obs	Mean	Std	Min	Max
$\ln GPK_{it}$	Logarithm of green patent knowledge width plus 1	9958	0.338	0.257	0	0.683
$\ln GPC_{it}$	Logarithm of the number of green patent citations within 2 years from the year of application plus 1	5510	1.289	1.160	0	6.397
$\ln SDETC_{it}$	Logarithm of the intensity of direct environmental target constraints plus 1	22275	0.356	0.372	0	1.224
$\ln SIETC_{it}$	Logarithm of the intensity of indirect environmental target constraints plus 1	22275	0.469	0.361	0	2.083
$\ln ER_{it}$	Logarithm of the frequency of environmental words in the Government Work Report as a proxy variable for environmental regulation to calculate the total proportion of environment-related words	22196	-5.187	0.346	-8.278	-4.011

$\ln GTE_{it}$	Logarithm of the proportion of science and technology spending in the general public budget plus 1	22275	0.040	0.023	0	0.188
$\ln CMA_N_{it}$	Logarithm of the number of negative news reported by the media plus 1	18148	4.057	1.112	0	10.038
$\ln CSR_{it}$	Logarithm of the comprehensive social responsibility score of Hexun-listed companies plus 1	18148	2.987	0.261	0	3.813
$\ln R\&D1_{it}$	Logarithm of R&D as a percentage of revenue plus 1	18148	0.043	0.054	0	3.668
$\ln R\&D2_{it}$	Logarithm of R&D as a percentage of total operating costs plus 1	18148	0.045	0.046	0	0.683
$\ln CDT_{it}$	Logarithm of the degree of enterprise digitization ⁵ plus 1, where the degree of enterprise digitization is obtained using a machine-learning-based text analysis of the annual reports of listed companies using Yuan et al.'s (2021) enterprise digitization glossary	18148	0.195	0.238	0	1.534
FC_{it}	SA index = $-0.737 \times \text{enterprise size} + 0.043 \times \text{enterprise size}^2 - 0.04 \times \text{enterprise age}$	18148	-3.812	0.310	-5.744	0
$\ln GDP_{it}$	Logarithm of per-capita GDP of prefecture-level cities (based on 2011 prices)	21275	11.378	0.539	9.219	13.056
$\ln HC_{it}$	Logarithm of the number of employees in scientific research comprehensive technology service industry (ten thousand)	22275	1.279	1.635	-3.912	4.273
$\ln FD_{it}$	Logarithm of the ratio of fiscal revenue to fiscal expenditure plus 1	22275	0.559	0.124	0	0.933
$\ln TI_{it}$	Logarithm of the mileage of roads in prefecture-level cities	22046	9.243	0.885	6.291	12.068
$\ln CS_{it}$	Logarithm of the total assets of listed companies	18148	22.389	1.496	16.161	31.036
$\ln LL_{it}$	Logarithm of the asset-liability ratio plus 1	18148	0.362	0.156	0	3.456
$\ln ROA_{it}$	Logarithm of the ratio of net income to average total assets plus 1	18133	1.110	0.037	-0.419	3.169
$\ln ROE_{it}$	Logarithm of the ratio of net income to average net assets plus 1	18133	2.711	0.036	-1.226	3.166
SOE_{it}	A dummy variable equal to 1 if the enterprise is a state-owned enterprise and 0 otherwise	18148	0.357	0.479	0	1
$\ln TQ_{it}$	Logarithm of the ratio of the listed firm's market value to the replacement cost plus 1	18112	0.936	0.505	0.002	5.267
$\ln FA_{it}$	Logarithm of net fixed assets over total assets plus 1	18148	0.186	0.128	0	0.670
$\ln LR_{it}$	Logarithm of current assets over current liabilities plus 1	18133	2.086	0.230	-0.141	5.351
$\ln EC_{it}$	Logarithm of the Lenard index ((operating income - operating costs - Selling expenses - administrative expenses)/operating income) plus 1	18148	0.098	0.150	-3.576	0.627
$\ln CFL_{it}$	Logarithm of net cash flow plus 1 over total assets	18133	1.901	0.166	-0.057	4.295

⁵ We measure the digitalization degree of micro enterprises by dividing the total frequency of digitalization-related words by the length of MD&A paragraphs in the annual report, multiplied by 100. The higher the index value, the higher the degree of digitalization of the enterprises.

5. Empirical results

5.1 Influence of local environmental target constraint intensity on enterprises' green innovation quality

According to Table 2, the coefficient of the influence of direct environmental target constraint intensity on $\ln GPK_{it}$ is not prominent, which indicates that the incentive effect of direct environmental target constraint intensity on enterprises' green innovation quality is not strong. The reason may be that direct environmental target setting focusing on specific pollutant emission reduction will prompt local governments to prefer command-based environmental regulation tools to meet mandatory emission reduction targets, and because of the existence of penalty caps and limited innovation compensation from improving the quality of green innovation, some enterprise are satisfied with "meeting the standards" of environmental standards. Moreover, when enterprises cannot obtain more revenue through green innovation, they will abandon their investment in high-quality green innovation and turn to strategic and responsive green innovation, or even low-quality green innovation with lower cost and difficulty to gain short-term benefits. In addition, based on the significance of the regression results of the quadratic term coefficients, it is clear that there is no significant nonlinear characteristic in the effect of the intensity of direct environmental target constraints on the quality of corporate green innovation.

Table 2 Benchmark Regression Results.

Variable	Model 1	Model 2	Model 1	Model 2
	$\ln GPK_{it}$	$\ln GPK_{it}$	$\ln GPK_{it}$	$\ln GPK_{it}$
$(\ln SDETC_{it})^2$		-0.041 (-1.18)		
$\ln SDETC_{it}$	0.005 (0.59)	0.037 (1.31)		
$(\ln SIETC_{it})^2$				-0.051** (-2.33)

$\ln SIETC_{it}$			0.017**	0.061***
			(2.07)	(2.96)
Control variables	YES	YES	YES	YES
Industry/city/year	YES	YES	YES	YES
Fixed effect				
N	8699	8699	8699	8699
R^2	0.2613	0.2614	0.2492	0.2497
F statistic	75.39	71.04	79.50	75.18

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Statistical value of T in parentheses.

619 The coefficient of indirect environmental target constraint intensity on $\ln GPK_{it}$ is significantly
620 positive, which shows that setting indirect environmental targets gives enterprises more freedom to
621 choose and stimulates active green innovation. Indirect environmental target constraint intensity, if
622 heightened, can effectively encourage enterprises to carry out high-quality green innovation.
623 However, the quadratic term coefficient is -0.051 at the 5% significance level, indicating that
624 indirect environmental target constraint intensity has an inverted U-shaped relationship with
625 enterprises' green innovation quality. Initially, indirect environmental target constraint intensity
626 will stimulate high-quality green innovations, but at a certain level of green innovation quality,
627 enterprises faced with higher indirect environmental target constraint intensity will have
628 decreasing marginal income from new, higher R&D investment as green innovation become
629 progressively harder. Therefore, the motivation for enterprises to improve green innovation quality
630 weakens continually. The positive influence of indirect environmental target constraint intensity on
631 enterprises' green innovation quality decreases marginally and progressively, which is in line with
632 Hypothesis 2. With an increase in the constraint intensity of indirect environmental targets,
633 enterprises are more prone to choose tactically contingent green innovations with lower costs and
634 less difficulty; consequently, enterprises' overall quality of green innovation will fall or even
635 become negative. Specifically, when $\ln SIETC_{it}$ reaches 1.196, the inverted U-shaped relationship
636 between indirect environmental target constraint intensity and enterprises' green innovation quality

reaches its apex. On the left side of the apex, indirect environmental target constraint intensity is positively correlated with enterprises' green innovation quality, while on the right side, they are negatively correlated. According to the variable statistics, when indirect environmental target constraint intensity exceeds the critical value for only very few samples, indirect environmental target constraint intensity still has stimulating effects on enterprises' green innovation quality. During 2011-2019, when rolling out environmental targets in Government Work Reports, local governments began to shift focus from direct environmental targets to indirect ones. Although this change in policies encouraged enterprises to carry out high-quality green innovations, we should note that the stimulating effects will weaken when the marginal income from R&D input to green innovation decreases progressively at later stages. We should be aware of the critical value of the indirect environmental target constraint intensity at the apex.

5.2 *Endogeneity and robustness tests*

We conducted robustness tests from three aspects: replacing the explained variables, accounting for city heterogeneity, and changing the regression methods. Specifically, (i) we replace $\ln GPK_{it}$ with $\ln GPC_{it}$; (ii) we remove sample enterprises from cities with better environmental quality, like Qingdao, Yantai, Lishui, Taizhou, Fuzhou, Xiamen, Shenzhen, Zhuhai, Huizhou, Zhongshan, Guiyang, and Kunming and rerun the regression; and (iii) using a panel interactive fixed effect model we control for fixed effects such as industry, city, and year, and further control the interactive industry-city, industry-year, and city-year fixed effects. Additionally, according to the requirement of correlation and exogeneity of instrumental variables, we (iv) use river density and annual precipitation as instrumental variables for the intensity of environmental target constraints and its quadratic terms, and conduct two-stage least squares (2SLS) regressions

on the intensity of local environmental target constraints and the quality of corporate green innovation. For the first three tests, we report the robustness test results in Table A.1. We provide the results of the instrumental variable estimation in Table A.2. The test statistics confirm the existence of endogeneity and the validity of the instrumental variables. The direction and significance of the regression coefficients from the robustness test and IV-2SLS regression are generally consistent with the baseline regression results, indicating strong support for the original findings.

5.3 Mechanism tests

The previous analysis concludes that direct environmental target constraint intensity has an insignificant influence on enterprises' green innovation quality; therefore, we analyze the transmission mechanism from only indirect environmental target constraint intensity to enterprises' green innovation quality. Based on Models 1 and 2, we build mediation models. Model 3 describes the influence of indirect environmental target constraint intensity on the intermediate variables, while Model 4 depicts how indirect environmental target constraint intensity influences enterprises' green innovation quality through the intermediate variables.

5.3.1 City-level tests

Based on the previous analysis of the theoretical mechanism, we test the two mechanisms of environmental regulation rigidity and governmental S&T expenditure. As Table A.3. shows, indirect environmental target constraint intensity prominently enhances the rigidity of environmental regulations and forms an inverted U-shaped relationship with enterprises' green innovation quality through environmental regulation rigidity. Comparing the $(lnSIETC_{it})^2$ coefficients in Models 2 and 4 reveals that environmental regulations create the inverted U-shaped

curve steeper between indirect environmental target constraint intensity and enterprises' green innovation quality. Moreover, indirect environmental target constraint intensity deterred governments from making more S&T expenditures, which negatively affected enterprises' green innovation quality. This is in line with Hypotheses 2 and 3.

5.3.2 Enterprise-level tests

We test the five micro-mechanisms of enterprises' media attention, social responsibility, R&D expenditure intensity, digitalization level, and financing constraints. According to Tables A.4. and A.5., indirect environmental target constraint intensity positively affects enterprises' green innovation quality by increasing negative news reports, strengthening their social responsibility, and boosting their R&D expenditure intensity. Then, indirect environmental target constraint intensity will relieve enterprises of financing constraints to encourage them to improve green innovation quality. Finally, indirect environmental target constraint intensity has an inverted U-shaped relationship with enterprises' digitalization progress. Because the digitalization level has positive effects on green innovation quality, indirect environmental target constraint intensity, by influencing the digitalization level of enterprises, has a steeper inverted U-shaped relationship with their green innovation quality. The test results comply with Hypotheses 4 and 5.

6. Further analysis

6.1 Change in enterprises' expected net income

To determine the source of the inverted U-shaped relationship between indirect environmental target constraint intensity and enterprises' green innovation quality, based on the theoretical mechanism and model analyses above, we continue using the intermediate effects model to observe changes brought about by boosted R&D input on expected net income under increasing indirect

environmental target constraint intensity. Sales profit is the major source of enterprise income; therefore, it can accurately reflect their income level. We add 1 to enterprises' sales revenue growth rate (RGR_{it}) and net profit margin (NPM_{it}) and take their logarithms ($\ln RGR_{it}$, $\ln NPM_{it}$). These explained variables represent enterprises' expected net income level. We use $\ln R\&D1_{it}$ and $\ln R\&D2_{it}$ as intermediate variables.

Table 3 summarizes the regression results. The influence of $\ln SIETC_{it}$ on $\ln RGR_{it}$ is significantly negative, as is the influence of $\ln R\&D1_{it}$ and $\ln R\&D2_{it}$ on $\ln RGR_{it}$. Considering the results of the mechanism analyses, we find that enterprises facing increased indirect environmental target constraint intensity will increase their R&D input, which will reduce the growth rate of sales revenue. This is mainly because as the intensity of the indirect environmental target constraint drives the increase in R&D investment, leading to an increase in the production and operation costs, coupled with the limited direct contribution of green innovation to sales revenue, the growth of sales revenue from green innovation has a marginal decreasing trend, resulting in a declining growth rate of sales revenue. Next, the coefficients of $\ln R\&D1_{it}$ and $\ln R\&D2_{it}$ in relation to $\ln NPM_{it}$ are significantly negative, which further proves that raised indirect environmental target constraint intensity will encourage enterprises to increase R&D expenditure intensity and consequently bring about a marginal and progressive decrease in their expected net income. After further observing the nonlinear influence of R&D expenditure intensity on the net sales profit margin, we find that the regression coefficients of $(\ln R\&D1_{it})^2$ and $(\ln R\&D2_{it})^2$ in relation to $\ln NPM_{it}$ are significantly positive, which proves the existence of a prominent U-shaped relationship between R&D expenditure intensity and net sales profit margin. Due to the long transition period of green patents, the increasing complexity of green innovation, and the cost of

R&D investment, especially high-quality green innovation, the return on sales revenue from R&D investment is not obvious in the early stage of R&D. When the intensity of R&D expenditure and technology level reach a certain level, the technology and achievements from the increased intensity of R&D expenditure mature and are converted into applications, which will significantly promote the increase in the net sales margin. In summary, the main reason behind the marginal and progressive decrease in the positive influence of indirect environmental target constraint intensity on enterprises' green innovation quality is that when enterprises face pressure from indirect environmental target constraint intensity, they will raise their R&D expenditure intensity to improve green innovation quality, which will consequently reduce their expected net income and weaken the incentive to improve green innovation quality.

Table 3. Influence of Indirect Environmental Target Constraint Intensity Increasing R&D Expenditure Intensity on Enterprises' Expected Net Income.

Variable	Model 4 $\ln RGR_{it}$	Model 4 $\ln RGR_{it}$	Model 4 $\ln NPM_{it}$	Model 4 $\ln NPM_{it}$	Model 4 $\ln NPM_{it}$	Model 4 $\ln NPM_{it}$
$(\ln SIETC_{it})^2$					-0.002 (-0.43)	-0.001 (-0.38)
$\ln SIETC_{it}$	-0.019** (-2.08)	-0.019** (-2.07)	0.010** (2.50)	0.010** (2.48)	0.011 (1.14)	0.011 (1.08)
$(\ln R\&D1_{it})^2$					0.539** (2.25)	
$\ln R\&D1_{it}$	-0.361*** (-3.77)		-0.252*** (-3.91)		-0.187** (-2.34)	
$(\ln R\&D2_{it})^2$						7.231*** (6.22)
$\ln R\&D2_{it}$		-0.449*** (-4.83)		-0.791*** (-9.51)		-1.673*** (-10.18)
CV	YES	YES	YES	YES	YES	YES
Industry/city/year fixed effect	YES	YES	YES	YES	YES	YES
Industry-city/industry-year/city-year interactive fixed effects	YES	YES	YES	YES	YES	YES
N	14712	14712	14608	14608	14608	14608
R ²	0.2143	0.2148	0.5893	0.5920	0.5894	0.5932
F statistic	119.20	119.85	789.92	800.87	702.59	716.00

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Statistical value of T in parentheses.

735

736 **6.2 Heterogeneity analysis**

737 Following Yu et al. (2020), we first examine age heterogeneity when local officials face
 738 promotion incentives. Mayors under 57 years of age will be more easily stimulated to obtain a
 739 promotion. Local governments and their officials are more proactive in implementing policies and
 740 measures; therefore, indirect environmental target constraint intensity has significantly positive
 741 effects on enterprises' green innovation quality. In contrast, in areas with mayors aged above 57
 742 years, the relevant departments lack patient encouragement, supervision, and review of patent
 743 quality, and environmental target constraint policies may not be implemented thoroughly.
 744 Therefore, their stimulating effect on enterprises' green innovation quality is insignificant.
 745 According to timeline of environmental target assessments written into the municipal and
 746 provincial Government Work Reports, we classify environmental target constraint policies into
 747 policies "prioritizing city over province" and policies "prioritizing province over city." In the
 748 former case, local officials are more proactive and internally motivated to roll out and firmly
 749 implement relevant policies and the quality-driven green development strategy. However, in the
 750 latter case, local officials in most cases will passively accept mandatory requests from upper
 751 authorities. Therefore, policies are better implemented in areas with policies "prioritizing city over
 752 province" than in areas with policies "prioritizing province over city."

Table 4 Regional Heterogeneity Analysis.

Variable	Mayor age ≤ 57		Mayor age ≥ 57		Prioritizing city over province		Prioritizing province over city	
	Model	Model	Model	Model	Model	Model	Model	Model
	1	2	1	2	1	2	1	2
$(lnSIETC_{it})^2$		-0.132*		-0.041		-0.052*		-0.084*
		**		(-1.09)		*		(-1.89)
		(-3.61)				(-2.05)		

<i>lnSIETC_{it}</i>	0.040** *	0.141** *	0.027 (1.21)	0.073 (1.54)	0.025** (2.34)	0.073** *	0.001 (0.59)	0.070* (1.76)
CV	YES	YES	YES	YES	YES	YES	YES	YES
Industry/city/year fixed effect	YES	YES	YES	YES	YES	YES	YES	YES
Industry-city/industry-year/city -year interactive fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
<i>N</i>	6710	6710	1636	1636	5468	5468	2763	2763
<i>R</i> ²	0.3634	0.3648	0.3663	0.3669	0.4015	0.4020	0.4452	0.4461
F statistic	25.69	24.90	9.97	9.38	47.11	44.46	21.07	20.00

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Statistical value of T in parentheses. Since direct environmental target constraint intensity has no significant regression results in this grouped heterogeneity analysis we do not report it here.

7. Conclusions and policy suggestions

Based on the unique characteristics of China's environmental responsibility system, this study innovatively constructs local environmental goal constraint intensity indicators based on actual evidence of local government environmental target constraint assessments by combining environmental policies with government environmental responsibility assessments. Based on a theoretical model that explores the impact of environmental target constraint intensity on enterprises' green innovation behavior, we empirically test the impact mechanism of different types of local environmental target constraint intensity on the quality of enterprises' green innovation using data of A-share listed companies in the Shanghai and Shenzhen markets from 2011 to 2019 and the Government Work Reports of each prefecture-level city. The analysis yielded several findings.

Indirect environmental target constraint intensity has significantly positive effects on enterprises' green innovation quality, though they have an inverted U-shaped relationship after further observing their nonlinear characteristics. The positive effects of indirect environmental target constraint intensity on enterprises' green innovation quality decrease marginally and

769 progressively; however, currently, the impact of indirect environmental target constraint intensity
770 on enterprises' green innovation quality is mostly facilitated. Direct environmental target
771 constraint intensity that aims to reduce the discharge of specific pollutants has insignificant effects
772 in improving enterprises' green innovation quality. Both the robustness tests and instrumental
773 variable regressions provide supporting evidence.

774 In the mechanism tests, indirect environmental target constraint intensity has an inverted
775 U-shaped trend by increasing the strength of environmental regulation and influencing the degree
776 of digitalization of enterprises, which in turn forms an inverted U-shaped relationship with the
777 quality of green innovation. In addition, the intensity of indirect environmental target constraints
778 will promote the quality of corporate green innovation by increasing corporate media attention,
779 corporate social responsibility, R&D expenditure intensity, and alleviating financing constraints,
780 but will also negatively affect the quality of corporate green innovation by suppressing government
781 S&T expenditure.

782 Further analysis reveals that, in the face of the indirect environmental target constraint intensity,
783 the increase in R&D expenditure intensity for green innovation quality improvement decreases the
784 expected net income, resulting in insufficient incentive for innovation quality improvement, which,
785 together with the increasing complexity of innovation, is an essential reason for the marginal
786 decreasing trend of the positive impact of the indirect environmental target constraint intensity on
787 the quality of green innovation of enterprises. Simultaneously, environmental target constraints
788 work better in areas with policies prioritizing cities over provinces and with mayors under 57 years
789 of age than in areas with policies prioritizing province over city and with mayors over 57 years old.

790 Based on these conclusions, we can propose the following suggestions to encourage enterprises

791 to improve green innovation quality, explore new paths of high-quality economic development
792 with a high level of ecological environment protection, and seek new dynamics of economic
793 growth:

794 **Improve the design of policies and systems.** Deepen the reform of the environmental target
795 accountability system, perfect the environmental target constraint system, take steps to establish
796 and improve the environmental target constraint system based on indirect environmental target
797 constraints and complemented by direct environmental target constraints. Attach special
798 importance to assessing the fulfillment of indirect environmental targets and release the fulfillment
799 in the next year's Government Work Report. Meanwhile, there should be more effort to review
800 enterprises' patents, scientifically and prudently patent authorization management systems to
801 prevent enterprises from conducting tactically contingent green innovations, and motivating
802 enterprises to shift focus from the quantity to the quality of green innovations.

803 **Inspire the internal motivation of enterprises.** We should diversify the mono-system that is
804 based on mandatory environmental regulations, strengthen the market orientation of green
805 innovations, and improve market-oriented environmental regulation instruments such as emission
806 rights trading mechanisms to increase compensation for enterprises' green innovations and
807 increase the incentives for improving green innovation quality. Meanwhile, in terms of green
808 patent quality and hardness and the realistic significance of green innovations, enterprises should
809 receive financial support and tax cuts or exemptions to alleviate their financial constraints, and
810 local governments should be guided to formulate strategies for long-term development by S&T
811 innovations, increase fiscal S&T expenditures, and encourage enterprises to enhance the intensity
812 and sustainability of R&D expenditure. In addition, the media attention on enterprises should

813 increase appropriately to enhance corporate social responsibility, and the investment and policy
814 support for the digital transformation of enterprises should be increased to enhance the technical
815 foundation and endogenous power of enterprises' green innovation quality improvement.

816 **Optimize policy implementation effects.** To deepen the reforms to streamline administration,
817 decentralize power, and improve services, local governments should consider local environmental
818 quality and green technology development to flexibly and proactively roll out a complete set of
819 detailed environmental targets adapted to local conditions, shoulder the corresponding
820 environmental responsibilities, and make and implement a quality-oriented green development
821 strategy. Meanwhile, localities can cultivate more young and knowledgeable cadres, be willing to
822 breach the inefficient tradition of promoting based on seniority and other regular promotion paths,
823 and breaking the constraints on departments, sectors, systems, and identifications so young cadres
824 can make the most of their talents. In addition, while the government strengthens the supervision of
825 enterprises, it should expand the support for enterprises' green innovation activities and enhance
826 internal incentives by publicizing, commending, and rewarding the heads of enterprises and R&D
827 personnel who obtain high-quality green innovation results. Additionally, there should be a
828 two-way exchange of political and corporate cadres and a stronger political association of
829 corporate executives, especially for enterprises in heavily polluting industries so environmental
830 target constraints have an optimal effect on the quality of corporate green innovation.

831 **Authors contribution** All authors contributed the conception and design of this study. The
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833 conceptualization and funding supporting were provided by Honggui Gao. The methodology
834 guidance and software supporting were provided by Yanan Hu and Qinan Ding; The project

administration and funding acquisition were provided by Yiding Tang. All authors read and approved the final manuscript.

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Declarations

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